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Quantifying the Effects of Climate Change on Simineh River Discharge in Lake Urmia Basin

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Abstract

The Simineh River is heavily reliant on water resources for agricultural aims in the Lake Urmia. However, the hydrological system of the Simineh basin is highly susceptible to the impacts of climate change scenarios, primarily due to the presence of diverse topographical features, limited availability of data, and the complex nature of the local climate. This study aimed to simulate the monthly discharge of the Simineh River using the SWAT and assess the effects of climate change on the monthly discharge. Future climate scenarios for the years 2011-2030 were generated using the HadCM3 weather models under the A2, B1, and A1B scenarios. After evaluating the performance of the LARS-WG model in producing precipitation, minimum and maximum temperatures for the Simineh River watershed, the output of the HadCM3 under the A1B, B1, and A2 scenarios reduced, and the desired meteorological parameters predicted. These predicted values used as inputs for the SWAT model. In this study, assuming no change in land use, the focus was solely on the impact of climate change scenarios. However, appropriate measures can be taken to save the Simineh River's water consumption by optimizing irrigation efficiency through innovative methods. This is crucial because the results indicate that a total reduction of up to 25% in discharge in the Lake Urmia basin under climate change leads to a significant decrease in the annual average inflow to the lake from 570 million cubic meters to 394, 398, and 440 million cubic meters under the A2, B1, and A1B scenarios, respectively. The Simineh River supplies 11% of the water in Lake Urmia, and taking necessary measures to conserve its water resources is essential.

Keywords: Discharge, Downscaling, Had CM3, LARS-WG, Iran, Simineh river, SWAT

INTRODUCTION

The main cause of climate change is the increase greenhouse gases in the atmosphere, as noted by various researchers (Nijssen et al., 2001; Nilawar and Waikar, 2019; Li and Fang, 2021). It is widely agreed upon by the scientific community that the temperature of the Earth is on the rise and this trend is predicted to continue (Li and Fang, 2017). As per the IPCC's Fifth Assessment Report, the global average temperature risen about 0.85 ◦C during the period of 1880-2012 (IPCC, 2013). To estimate the possible impacts of climate change on water resource systems, it is necessary to have precise forecasts of critical meteorological variables like temperature and precipitation, which can fluctuate significantly at the regional or local level, as stated by Horton et al. in 2006. To generate predictions for such meteorological variables, scientists often rely on climate change projections produced by coupled AOGCMs or RCMs that are driven by AOGCM outputs. AOGCMs offer a global outlook while RCMs are intended to capture regional-scale climate patterns with increased spatial resolution. Therefore, RCMs are generally deemed more effective in describing regional-scale climate and can provide more precise and accurate forecasts of such meteorological variables. However, it is essential to recognize that both AOGCMs and RCMs have limitations, and their projections should be used with caution while making decisions related to water resource systems. It is important to acknowledge that the development of precise climate change projections is a dynamic field, and ongoing research is dedicated to enhancing the accuracy and reliability of these projections. Staying up-to-date on the latest advancements in weather modeling and refining approaches for evaluating the potential impacts of climate change on water resource systems is essential for researchers. Staying informed about these advancements can guarantee the precision and efficacy of models and methodologies, leading to improved decision-making and management of water resources amidst the changing climate. Due to the intricate and nonlinear nature of the climate system, different experiments using AOGCMs or RCMs may yield varying results for the same emission scenario. This variability can be attributed to several factors, including differences in model design, assumptions, and input data. The use of different AOGCM or RCM experiments can lead to significant uncertainty in climate projections, as noted by researchers such as Frei et al. in 2003, Rais et al. in 2004, and Horton et al. in 2006. While RCMs are generally deemed more dependable for regional-scale climate projections compared to AOGCMs, the uncertainty introduced by RCMs cannot be disregarded entirely. Nevertheless, studies have demonstrated that the inter-model variability of RCMs is generally lower than that of AOGCMs, as reported by Jenkins and Lowe in 2003.

The IPCC predicts that the global average temperature will continue to rise by 0.3 ◦C to 0.7 ◦C during 2016–2035, with a projected increase of 1 ◦C under the low scenario and over 4 ◦C under the high scenario by the end of the 21st century, according to various studies, including Milly et al. in 2005, UNFCCC in 2015, Marahatta et al. in 2021, Masson-Delmotte et al. in 2021, and Wang et al. in 2022. The rise in temperature has caused a rapid increase in evapotranspiration rates, resulting in notable modifications to worldwide precipitation patterns (Wang et al., 2013; Paparrizos et al.,2015; Zhang et al., 2016; Zhang and Villarini, 2017; Lehner et al., 2017; Li and Fang, 2021). Furthermore, according to Bajracharya et al (2018), the global average surface temperature will increase and precipitation patterns will change in the coming century. It is predicted that the hydrological cycle will be impacted by climate changes, as the altered temperature and precipitation patterns affect the distribution of water cycle components such as evaporation, precipitation, soil moisture, and runoff (Rabezanahary et al., 2021; Liu et al., 2022; Wang et al., 2022). Understanding about river flow response to climate change is essential for effective planning and management of water resources. Several studies have indicated that the discharge of one-third of the world's rivers have change since the 1950s (Tan and Gan, 2015; Bhatta et al., 2019; Lehner et al., 2019). In previous modeling studies, a common approach to use a unit increase in temperature and a percentage change in precipitation as input for weather models, or to adjust the output of the weather model by revising observed station data. While this approach may reduce bias in the weather model, not fully account for changes in the intensity and frequency of precipitation that occur due to climate changes (Liu et al., 2013; Fan and Shibata, 2015; Steinschneider et al., 2015). To overcome this limitation, many studies have employed a combination of GCMs and hydrological models to assess the potential impact of climate change on river flow (Wang et al., 2018). To account this uncertainty, researchers often use a various GCMs to provide better assessments of water resources. Downscaling techniques such as dynamic or statistical methods are then employed to adapt the spatio-temporal resolutions of hydrological models and GCMs. Based on different scenarios in climate changes, temperature and precipitation are procreated as input data for SWAT and other hydrological models to anticipation future discharge. This is regarded as most important methods for evaluating discharge and runoff changes (Tan et al., 2017; Luo et al., 2018; Bhatta et al., 2019; Xu, 1999). The SWAT is a semi-distributed and physical-based model in basin-scale that is well-suited for assessing the reply of runoff and discharge to precipitation and temperature changes. Many researchers have employed the SWAT model to evaluate the impact of precipitation and temperature changes on runoff and water resources in different areas. For example, Pongpetch et al. (2015) employed the SWAT to simulate discharge, flow and sediment in Thailand. In 2017, Golmohammadi et al. used this model to predict runoff-generating regions in Ontario, Canada, providing a source for modeling runoff generation in the watershed. Jung et al. (2018) applied the SWAT to estimate the influence of CO2 changes on the hydrological cycle in Korea. Bhatta et al. (2019) used the SWAT and four RCMs to evaluate the effects of precipitation and temperature change on the hydrology on Himalayan river. Lucas-Borja et al. (2020) utilized the SWAT model to simulate and predict runoff in a small watershed in the tropical forest of Brazil and found a decreasing trend in the watershed runoff. Amin et al. (2020) applied the SWAT model to simulate the runoff of the Mojo river in Korea.

This study aimed to evaluate the impact of future climate changes on discharge in the Simineh river. The study findings contribute to the existing literature on streamflow changes in the region due to global warming. Additionally, this study provides valuable scientific insights for river basin management to mitigate potential water resource problems in the lake Urmia basin in the future. The study also has significant implications for water resources management in the lake Urmia Basin, as it can inform policymakers and water resource managers in the region about the potential effects of climate change on streamflow. Understanding how streamflow may change in the future is essential for developing effective strategies to manage and sustain water resources in the region and mitigate any potential adverse impacts on agriculture and other sectors that rely on water resources.

2 Materials and method

2.1 Study area

The Simineh river, located in the N38 zone, and is situated in the south of Lake Urmia in Iran (Fig 1). The basin covers an area of 3860 km2, which represents approximately 27% of the northern Karun river basin. It flows into Lake Urmia to the north and the Karun river basin to the south. The Simineh river originates from the mountains surrounding Saqqez (near Zanjan and Terejan) in the south of Lake Urmia. The general slope of the basin is towards the northwest, and Most of the basin consists of flat topography, with slope gradients of less than 9% (Fig. 2-b). The elevation of the basin ranges from 1267 meters at the outlet to 2559 meters in the southwest highlands of the basin (Fig 2-a). The annual precipitation varies from approximately 231 mm to 848 mm, and the minimum and maximum temperatures in the basin are 11°C and 18.1°C, respectively. The Simineh river flows approximately 200 km from the mountains of Kurdistan in Iraq and Iran.

The Simineh river comprises five distinct land use types, as depicted in Figure 2-c. The dominant land use category is agriculture land (AGRL), accounting for 79.43% of the basin area, followed by grass land (PAST) at 6.16%, and forest land (FRST) at 3.29 %, and land for construction (URML) at 1.10%. The Simineh river basin encompasses a variety of land use types and soil compositions, including five distinct soil types (as depicted in Figure 2-d). The soil in the study area includes two types of soils, Aridisols and Inceptisols, typically found in four different layers, often accompanied by rock outcrops. The most prevalent soil texture within the basin is L-GR-FSL-GRV-COS with B hydrologic group, which covers approximately 37.69% of the total area. HOGBACK (with STV-FSL-FSL-UWB texture and C hydrologic group) comprise 36.86% of the soil types, while CASTILE (with GR--L-GRV-SL-GRV-S texture and B hydrologic group) and GROTON (with GR--SL-GR--SL-GRV-LS-GRX texture and A hydrologic group) cover 16.38% and 6.83% of the area, respectively. TIOGA (with FSL-GR--FSL-GRV-LS texture and B hydrologic group) covers only 2.23% of the basin area. In summary agriculture is the primary land use within the basin, with a predominant focus on farming activities.

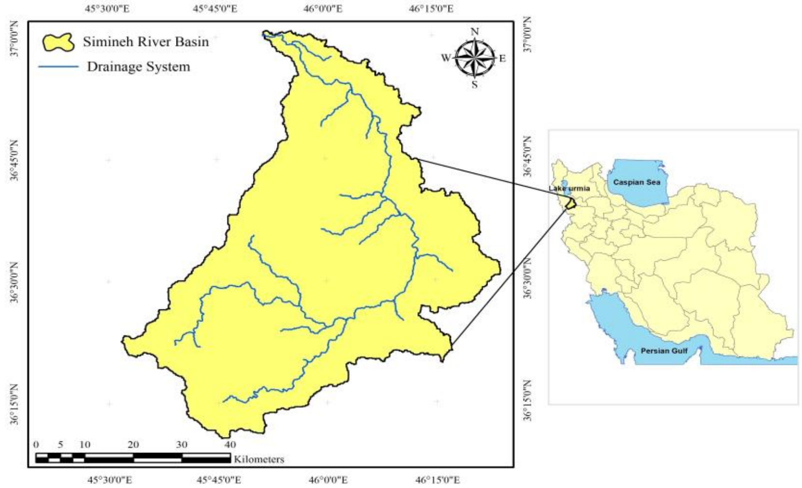

Figure 1. Location of the study area and river monitoring network.

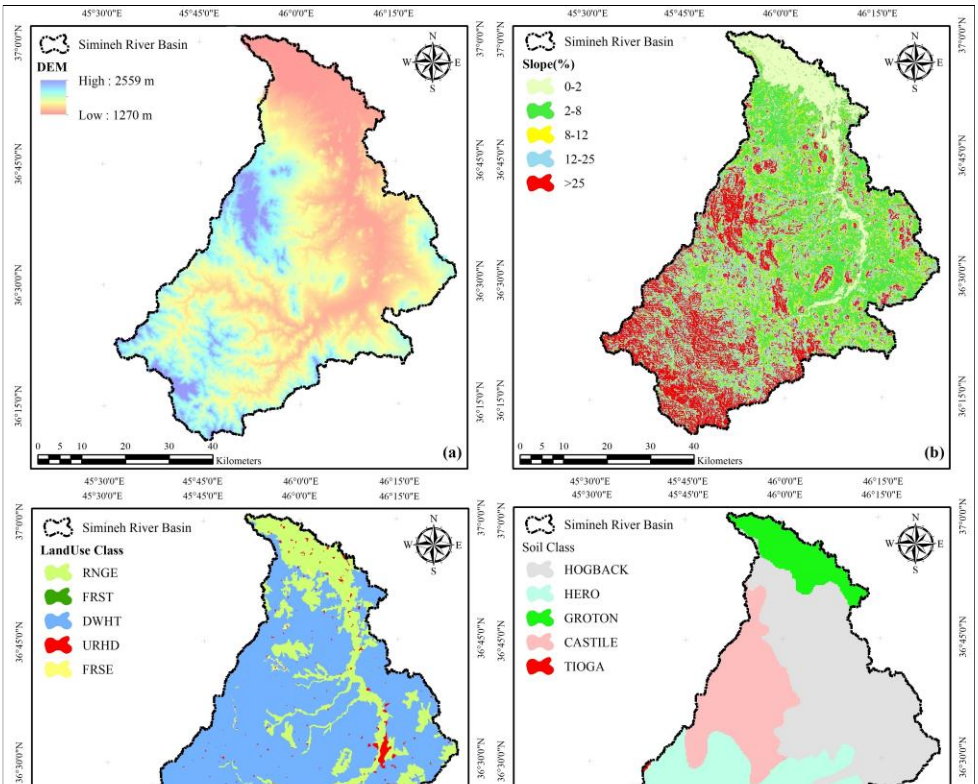

Figure 2. Characteristics of (a) DEM, (b) Slope, (C) land use, and (d) soil.

2.2 SWAT Model

The mainframe of water resources management under climate change is about the incorporation of the operational water projects in the planning horizon, policies, and macro-future decisions. However, when the allocation of water resources by neglecting climate change is performed, the results will not have the necessary validity and accuracy in practice (IPCC et al., 2007). Accordingly, examining the reliability of water supply in satisfaction of water demand for agricultural, industrial, drinking, and environmental uses; in addition to, allocation of the available water based on the predefined or dictated governmental rules for different sectors with consideration to the climate change and operational water projects is inevitable. Such applications are frequently addressed by the applications of the soil and water assessment tool (SWAT) and the river basin simulation, that showed promising results. SWAT (Arnold et al., 1998), as a basin-wide and well-established hydrologic model, is frequently used for simulating the streamflow process, especially in evaluation of inflows and outflows from the reservoir or the river-basin. This process-oriented model can simulate the hydrological processes based on the soil and water interactions and then develops estimations based on the changes of hydrologic variables in the allocated basin (Arnold and Fohrer, 2005). Due to the no-charge modeling, simultaneous simulation of hydrological variables, and agricultural management in complex basins with various land use and soil types, many studies endorsed the application of SWAT (Ahmadzadeh et al., 2016).

SWAT includes approaches describing how CO2 concentration, precipitation, temperature, and humidity affect plant growth, ET, snow, and runoff generation, and has often been used as a tool to investigate climate change effects. Several case studies of climate change impacts on water resources have used this model (e.g., Hanratty and Stefan, 1998; Rosenberg et al., 1999; Cruise et al., 1999; Stonefelt et al., 2000; Fontaine et al., 2001; Eckhardt and Ulbrich, 2003; Chaplot, 2007; Schuol et al., 2008). SWAT has been used to model portions of the San Joaquin watershed (Flay and Narasimhan, 2000; Luo et al., 2008). Often-used hydrologic models for IWRM include: Soil and Water Assessment Tool (SWAT), a watershed modelling code that simulates the principal hydrologic fluxes at a daily time step (Arnold et al., 1998). The key indicators of floods, namely runoff, flood peaks, and precipitation, were assessed in this study. The SWAT model was utilized for this purpose as it can effectively simulate changes in regional runoff (Arnold et al., 1998; Shrestha et al., 2018; Bhatta et al., 2019). The model comprises three main components, including the hydrological cycle runoff process, slope confluence land process, and river confluence process (Konapala et al., 2016). The hydrological process on the surface was divided into two parts, namely land hydrological cycle and river confluence process (Osei et al., 2019; Ballesteros et al., 2020; Tanteliniaina et al., 2021; Li and Fang, 2021; Liu et al., 2022). The simulation of the land hydrological cycle was primarily based on the water balance equation represented by Equation (1):

$$SW_t = SW_0 + \sum_{i=1}^{t} (R_{day} - Q_{surf} - E_{surf} - W_{seep} - Q_{gw}) \quad (1)$$

In Equation (1), *SWt* represents the final soil moisture content, *SW0* represents the initial soil moisture content in millimeters (mm), t represents the time step in days, Rday represents the rainfall on the *i-th* day, *Qsurf* represents the surface runoff on the *i-th* day in mm, *Ea* represents the evaporation on the *i-th* day in mm, *Wseep* represents the infiltration and lateral flow at the bottom of the soil profile on the *i-th* day in mm, and *Qgw* represents the groundwater outflow on the *i-th* day in mm.

To estimate surface runoff, the SWAT model employs the SCS-CN method and the Green-Ampt and Ampere infiltration methods. The SCS model was developed to estimate runoff for various land uses and soil hydrologic groups. The Green-Ampt and Ampere equations assume the presence of excess water on the surface at all times to predict infiltration. The SCS equation for estimating surface runoff is given by:

$$Q_{swf} = \frac{\left(R_{day} - I_a\right)^2}{\left(R_{day} - I_a + S\right)} \quad (2)$$

In equation (2), *Ia* includes tracking, infiltration, and surface storage for the day in millimeters of water (H2O), that represents the initial abstraction, while *S* represents the retention factor. The coefficient of surface retention depends on various factors such as soil type, vegetation cover, land use, elevation, and slope. The parameter *S* is defined as equation (3), where *CN* indicate the curve number.

$$S = 25.4(\frac{1000}{CN} - 10) \quad (3)$$

Dividing the sub-basins into branches is necessary for building the model and the simulation verification process. To achieve this, topographic data was filled in to reduce errors caused by various landforms. Then, homogeneous hydrological units (HRUs) were determined by dividing each sub-basin into several HRUs based on features such as land use, soil, and slope. The more accurate the unit division is, the higher the simulation accuracy, but the model calculation speed must be maintained. Ultimately, the Upper Simineh river basin was divided into 27 HRUs, as depicted in Figure 3.

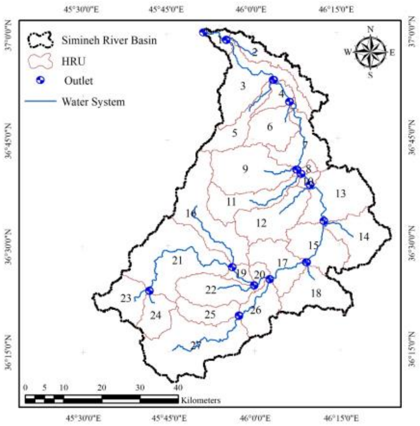

Figure 3. HRU division of Simineh river

2.3 Model parameter sensitivity, calibration, and validation

The hydrological sensitivity of watersheds varies significantly based on their conditions and characteristics, making them sensitive to specific parameters. Full calibration details can be found in Luo et al. (2008). The most sensitive model parameters were chosen in the calibration procedure based on literature review and a preliminary sensitivity analysis (Luo et al., 2008). According to studies in this field (such as Ficklin et al., 2009; Yuanet al., 2015; Chen et al., 2020; Liu et al., 2022) 20 of the most sensitive parameters selected and incorporated into the model for calibration. In the initial stage of calibration, the sensitive parameters identified, and further calibration conducted with a focus on these parameters. The sensitivity rankings of the parameters are listed in Table 1.

Table 1. The sensitive parameters for streamflow with their ranges and adopted values.

Rank	Parameter	Description	Range	Adopted value	P-value	t-Stat
1	ESCO.hru	Soil evaporation compensation factor	0-5	2.67	0.00	4.82
2	SMTMP.bsn	Snowfall temperature	-10-10	9.50	0.00	3.41
3	SOL_K.sol	Saturated hydraulic conductivity	-0.9 – 0.9	0.69	0.00	2.86
4	SLSUBBSN.hru	Average slope length	0-100	13.5	0.02	2.33
5	SURLAG.bsn	Surface runoff lag time	0-24	8.04	0.04	-1.99
6	SOL_AWC.sol	soil available water storage capacity	0-1	0.65	0.05	-1.94
7	ALPHA_BF.gw	Base flow alpha factor	-1-1	0.85	0.05	1.93
8	SMFMX.bsn	Maximum melt rate for snow during the year (occurs on summer solstice)	-10-10	-3.30	0.10	-1.62
9	SOL_BD.sol	Moist bulk density of first soil layer	0-10	6.45	0.11	1.59
10	SOL_Z.sol	The thickness of soil layers	1-5	1.18	0.14	-1.46
11	CH_K2.rte	Effective hydraulic conductivity in the main channel	0-100	35.5	0.23	-1.19
12	ALPHA_BNK.rte	Base flow alpha factor for bank storage	0-1	0.38	0.24	-1.17
13	EPCO.hru	Plant absorption compensation factor	0-5	2.27	0.3	1.04
14	GWQMN.gw	Threshold depth of water in shallow aquifer for return flow to occur	0-1	0.12	0.43	-0.79
15	CN2.mgt	SCS runoff curve number	-0.1–0.1	0.04	0.43	0.78
16	REVAPMN.gw	Threshold depth of water in the shallow aquifer for “revap” to occur	0-1	0.70	0.44	0.76
17	TIMP.bsn	Stack snow temperature delay factor	0-1	0.47	0.48	0.70
18	SMFMN.bsn	Minimum melt rate for snow during the year (occurs on winter solstice)	-10-10	-0.1	0.49	-0.68
19	SFTMP.bsn	Snow melting temperature	-10-10	-3.30	0.73	0.34
20	GW_DELY.gw	Groundwater delay time	0-10	8.65	0.94	-0.07

To ensure the accuracy of the SWAT model, sensitivity analysis, calibration, and validation were performed. Calibration used daily data from 1986-2000, with the first two years used as a warm-up period, while validation was performed on data from 2001-2010. SWAT-CUP was used for calibration and uncertainty analysis, while the Sequential Uncertainty Fitting algorithm (SUFI-2) was used for sensitivity analysis, calibration, validation, and uncertainty analysis in the Simineh River basin. Performance of the model was evaluated using the coefficient of determination (R2), the Nash-Sutcliffe efficiency coefficient (NS), percent bias (PBIAS), the P coefficient, and the r coefficient. These measurements were used to verify whether the SWAT model was satisfactory for use in the study.

2.4 Future climate change projection

Two main climatic factors that influence discharge on a basin scale are temperature and precipitation (Wang et al., 2018). The Lars-WG model used to correct the future climate data for 2011-2030 under A2, B1, and A1B scenarios. This downscaling technique is commonly used and relatively simple, and it can cluster the entire range of various models and calculate their average level (Li and Fang, 2021). The mean changes in temperature and precipitation for the 2020s (2011-2030) A1B under, B1, and A2 scenarios compared to the baseline period (1986-2010). In order to predict the impacts of future precipitation and temperature changes on discharge in monthly scale, the calibrated SWAT model used. precipitation and temperature data generated by LARS-WG method under A2, B1, and A1B scenarios introduced as input to SWAT model.

3 Results

3.1 Projected changes in precipitation and temperature

3.1.1 Precipitation

The trend of precipitation changes in the 2020s compared to the 1986-2010 period does not show uniformity. The HadCM3 model indicates lower precipitation in some months and higher precipitation in other months of the future period compared to the baseline period. All three scenarios predict an increase in rainfall for February, March, September, October, November, and December, and a decrease in rainfall for April, July, and August. The A2, B1, and A1B scenarios predict the highest increase in rainfall for November. The scenarios have shown different changes in January, May, and July. In conclusion, the average annual precipitation in the Simineh river watershed will increase in the 2020s. The predicted average annual precipitation for this decade under the A2, B1, and A1B scenarios will be 468.48, 488.84, and 469.79 millimeters, respectively, while the annual precipitation during the baseline period was 453.47 millimeters. Therefore, the study area will experience an increase in precipitation ranging from 8.78% to 12.86%, depending on the scenario. (Figure. 4).

3.1.2 Temperature

Figure 4 shows the average minimum temperature of the study watershed in the 2020s compared to the 1986-2015 period. All three scenarios (A2, B1, and A1B) predict an increase in minimum temperature in all months. The A2, B1, and A1B scenarios predict an increase in minimum temperature of 0.1-1.27°C, 0.2-1.12°C, and 0.1-0.31°C, respectively. The highest increase in temperature will occur in February and the lowest in October. It can be observed that the A2 scenario predicts a higher increase in temperature compared to the other scenarios.

Furthermore, all three scenarios predict an increase in maximum temperature for all months. By comparing the maximum temperature of the observed period and the 2030-2011 period, it can be observed that the highest increase in maximum temperature will occur in August, ranging from 0.83°C to 0.95°C. The lowest increase will occur in January, ranging from 0.1°C to 0.3°C. It is also observed that the A2 scenario predicts a higher increase in temperature compared to the other scenarios (Figure 4).

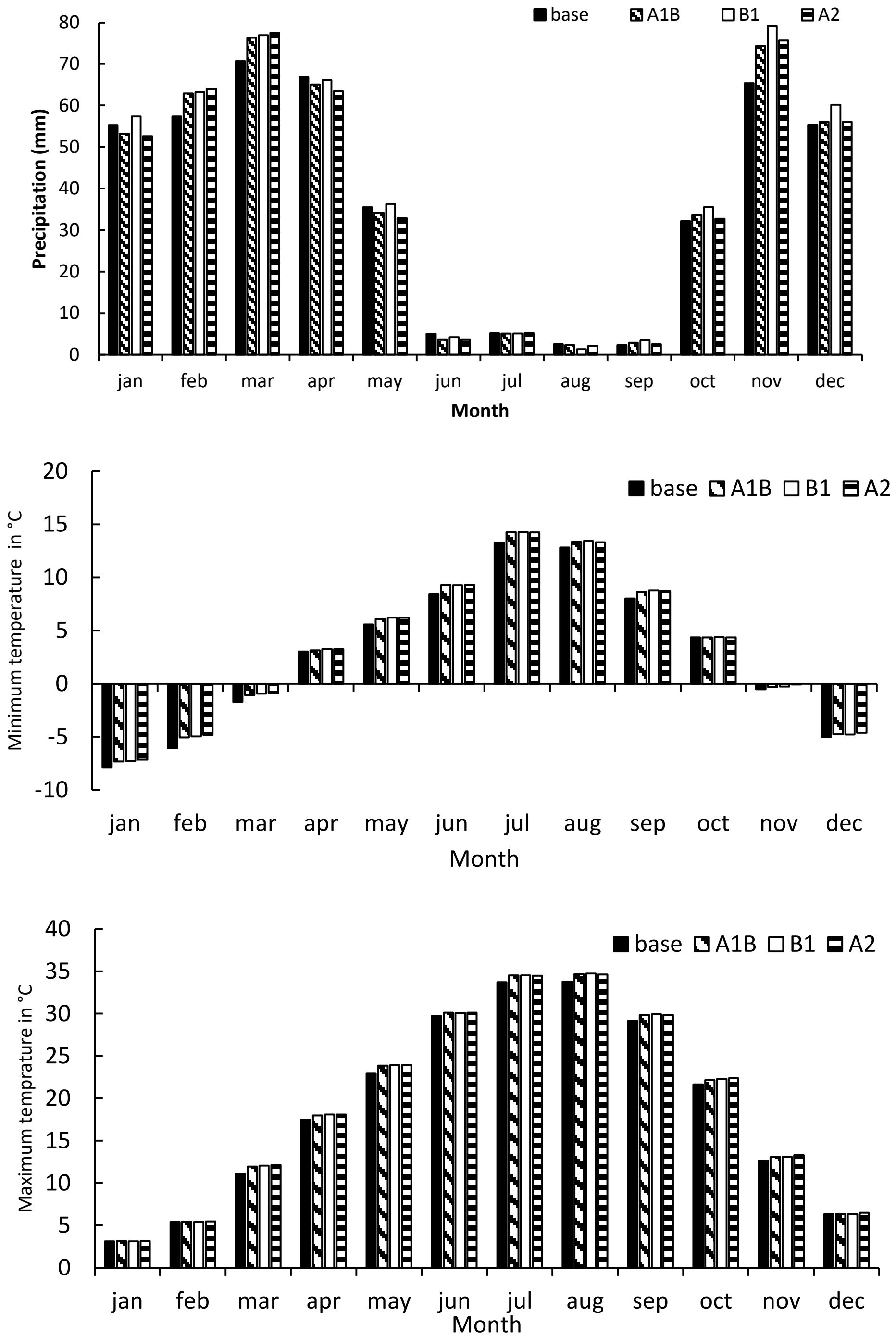

Figure 4. Monthly precipitation, Minimum temperature, and Maximum temperature during the baseline (1986–2010) and 2020s periods under A2, B1, and A1B scenarios.

3.2 Parameter sensitivity, calibration, and validation

Twenty parameters selected for calibration of the model, as shown in Table 1. The sensitivity of parameters is measured using two factors, P-Value and T-Stat. A parameter is considered sensitive if changes in its value significantly affect the output results (Tuo et al., 2016; Li and Fang, 2021). The sensitivity of a parameter is determined based on its P-Value, where a parameter with a value closer to zero is more sensitive and ranks first in the sensitivity ranking (Abbaspour, 2008). In terms of T-Stat, a parameter with a higher absolute value is more sensitive (Abbaspour, 2008; (Abbaspour et al., 2017). Based on the mentioned factors, the soil evaporation compensation factor (ESCO.hru) had the most significant impact on the output flow rate, while the groundwater delay time (GW_DELY.gw) had the least impact. During the calibration period (1986-2000), the simulated monthly streamflow values compared to the observed values (Figure.5). The R2 value is equal to 0.65, and the NS values is equal to 0.62, respectively (Table 2). The PBIAS value is equal to 18.75%, indicating that the simulated values were generally lower than the observed values. During the validation period, the R2 and NS values equal to 0.57, and 0.48, respectively. The PBIAS value is equal to 19.2%, and the R2 and NS values during this period were slightly lower than those during the calibration period.

According to Tables 2, the results obtained from the objective functions found to be satisfactory. Nash and Sutcliffe (1970) showed that the Nash-Sutcliffe coefficient (NS) values greater than 0.75 are considered good, and if the value of NS is greater than 0.50, the simulation model can be considered good, but if it becomes negative, it is better to rely on observed data rather than the model results. Based on the obtained results, it is evident that the model had weaknesses in simulating streamflow. This could be attributed to various factors, such as errors in observed data, errors in input data, and insufficient number of stations in the study area. Given that hydrological simulation of a watershed is subject to significant uncertainty, it is necessary to prepare model inputs with sufficient accuracy to obtain good results.

Table 2. Statistical performance for the calibration and validation periods.

Stage	R2	NS	P-factor	R-factor	PBIAS	MSE
Before calibration	0.44	0.39	0.10	0.00	22.2	28.6
Calibration	0.65	0.62	0.43	0.44	18.75	18.2
Validation	0.58	0.47	0.41	0.40	19.4	12.8

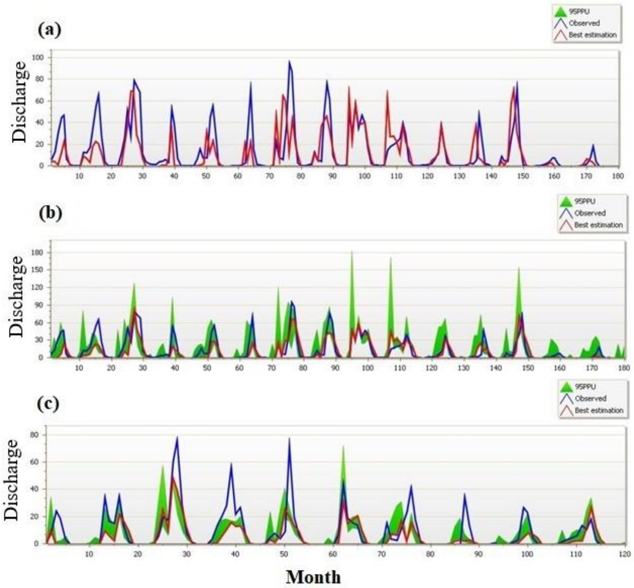

Figure 5. Comparisons between observed and simulated streamflow at Dashband station on the monthly time steps for (a) before calibration (b) calibration and (c) validation.

3.3 Changes in the discharge on Simineh river basin under climate change

In this study, using the SWAT model and under climate change conditions, the changes in monthly input flow to the lake were compared for the benchmark and future scenarios under the A2, B1, and A1B emission scenarios, for the Dashtband-e-Bukan watershed station. The results show a significant decrease in flow in March, April, May, June, July, August, September, and October, which is more pronounced under the A2 scenario. In the other months, the monthly mean flow has slightly increased, but overall and on an annual scale, all three scenarios predict a decrease in flow (Figure 6). The annual flow values for the 2030-2011 period, under the A2, A1B, and B1 scenarios, are 66.8, 73.8, and 73.9 cubic meters per second, respectively, while this value was observed to be 51.12 cubic meters per second for the baseline period. Table 3 shows the monthly flow values for the future and baseline periods.

4 Conclusions

This study was conducted to investigate the impact of climate change on discharge in the Simineh river basin. This basin is one of the important river basins on Urmia Lake basin. In general, the simultaneous increase in maximum and minimum temperatures could lead to significant temperature increases in the region in the future. The predicted mean temperature for the 2020s under the A2, B1 and A1B scenarios will be 11.49, 11.45 and 11.40 degrees Celsius, respectively. These results are somewhat consistent with other studies which predicted a temperature increase for different basins and synoptic stations (Furuya and Koyama, 2005; Aggarwal et al., 2010; Arunrat et al., 2018; Farokhzadeh et al., 2018; Mansouri Daneshvar et al., 2019; Sharafati et al., 2020; Doulabian, et al., 2021). The SWAT model calibrated and validated using observation data from 1986 to

2000 and 2001 to 2010 respectively, and finally the model was prepared to predict flows for future decades under climate change scenarios. The results indicate a decrease in peak flow and flood volume on an annual basis due to decrease in precipitation in the 2020s. Comparison of the results with research around the world (Bekiaris, 2005; Feyreisen et al., 2007; Wang et al., 2018; Abou Rafee et al., 2019) shows that although there are many challenges related to simulating hydrological characteristics and basin inputs, the simulation accuracy is acceptable and is consistent with the results of other researchers' studies.

This study provides useful information about the current and future river flow of the Simineh river based on climate change scenarios and can benefit from the results of this research in more precise planning of water resource and Urmia Lake revival projects. The results show an overall reduction of up to 25 percent in the water resources of the basin solely under climate change scenarios. Based on the results of the research, it is necessary to pay more attention to the problems of Lake Urmia. In climate change studies, uncertainties affect the simulation of climate variables by AOGCM models and the correction of the output of these models for application in simulating various systems including water resources at different stages. These sources of uncertainty include uncertainty in emission scenarios, uncertainty in converting greenhouse gas amounts to atmospheric concentration and radiative forcing, uncertainty related to the sensitivity of different AOGCM models to the same radiative forcing, uncertainty related to the simulation of AOGCM models at regional levels and uncertainty in downscaling methods (Ahmadalipour et al., 2017; Minville et al., 2008; Ouyang et al., 2015). Thus, it can be said that the output of hydrological simulation models under climate change have sufficient accuracy for decision making when the uncertainties related to the mentioned cases are applied and analyzed in the relevant calculations. Considering the sources of uncertainty in future studies and using the outputs of the fifth IPCC report is suggested. Since a significant part of the study area is agricultural lands and the livelihood of a large part of the basin dwellers depends on agriculture, and in this season, there is a need for water resources for irrigation of agricultural lands and drinking more, the need for management and planning to preserve water resources and measures appropriate to future changes indicates. Management planning to extract and store water in rainy seasons, development of new water supply methods, use of water consumption and efficiency increasing methods are recommended.

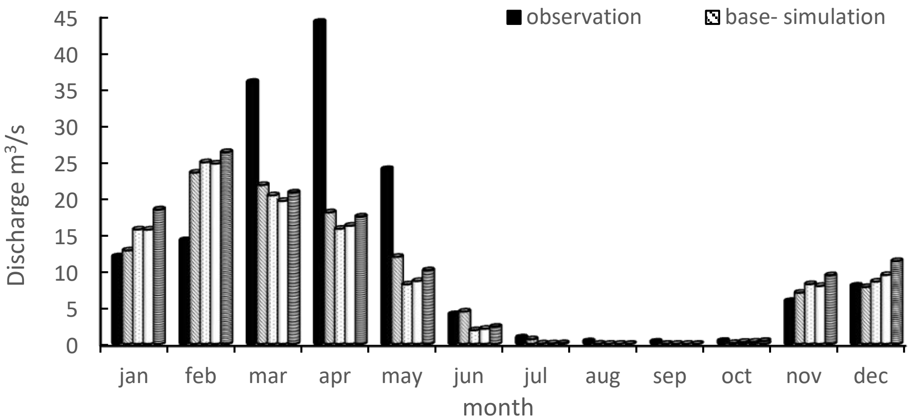

Figure 6. Monthly discharge during the baseline and 2020s periods under climate change scenarios.

Table 3. Monthly and Annual discharge during the baseline (1986–2010) and 2020s periods under A2, B1, and A1B scenarios.

Month	Observation	Simulation	A2	A1B	B1
Jan	12.01	12.83	15.71	15.69	18.46
Feb	14.24	23.51	24.93	24.75	26.33
Mar	35.93	21.81	20.40	19.63	20.79
Apr	44.16	18.06	15.80	16.23	17.49
May	23.99	11.94	8.17	8.63	10.10
Jun	4.08	4.43	1.87	2.07	2.34
Jul	0.88	0.63	0.05	0.06	0.08
Agu	0.35	0.01	0.00	0.00	0.00
Sep	0.29	0.00	0.00	0.00	0.00
Oct	0.40	0.11	0.27	0.30	0.40
Nov	5.88	7.02	8.20	7.95	9.42
Des	7.99	7.80	8.55	7.46	11.37
Annual	12.52	9.01	8.66	8.73	9.73

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